The implications of a price anchoring effect at the upstairs market of the London Stock Exchange

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Abstract: This paper studies the upstairs market of the Stock Exchange Trading System (SETS) of the London Stock Exchange (LSE). We hypothesise that the implicit interaction between the upstairs and the downstairs market at the LSE alters the pricing mechanism at the upstairs market. We show that in the upstairs market, market makers resort to "cluster undercutting" practices on the basis of a notional minimum price increment that resembles an anchoring-and-adjustment effect. In particular, we report that liquidity providers consistently buy just below the implicit minimum price increment and consistently sell just above it. This finding is strongly related to stock-price momentum and periods of increased trade intensity. Overall, this effect has only a weak connection to differences in informed trading and is mostly related to the notional price barriers and resistance levels introduced by the minimum tick size of the order book.

Keywords: Informed trading,; Microstructure, Upstairs market, LSE; High-Frequency data

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1. INTRODUCTION

The London Stock Exchange (LSE)'s main trading platform, the Stock Exchange Trading System (SETS), is a hybrid market with an electronic order book and a decentralised upstairs market. The upstairs market involves dealers who, in contrast to those at the New York Stock Exchange (NYSE), have no obligation to offer quotes on the order book. Trades at the upstairs market are privately negotiated and there are no minimum tick restrictions. This paper shows that market makers often take advantage of this institutional setting and employ "cluster undercutting" practices (see Bhattacharya et al., 2012), hence stepping ahead of other liquidity suppliers.

In particular, we examine to what extent investors submitting orders at the LSE upstairs market formulate their pricing based on their beliefs of the information they hold from the downstairs market. The main motivation of this paper lies in Tversky and Kahneman's (1974) anchoring-and-adjustment heuristic which refers to individuals anchoring their beliefs in a subjective probability distribution. We argue that this probability distribution is predetermined by the minimum tick size rules that apply in the order-book market but are not obligatory when trading at the upstairs market. We find that the institutional setting and the absence of minimum tick size regulations offer scope to market participants to use the implicit minimum tick as a threshold price in the upstairs market. In other words, the minimum tick in the order book serves as an anchor for market makers' price setting in the upstairs market. However, price adjustments are then made to trade above and below this "anchor".

The literature relating to behavioural biases in asset pricing has shown that one bias that is prevalent in financial markets is price clustering: the tendency of investors to concentrate their terms of trading in a specific set of prices. Goodhart and Curcio (1991) suggest that order preference, the natural attraction of individuals towards round numbers, may explain asset price clustering to some extent. In a similar context, Bhattacharya et al. (2012) report that studies on financial markets have underestimated (overestimated) the significance of the final digits 1 and 9 (0 and 5) and that a "reverse clustering" effect, the tendency to cluster prices around focal numbers, similar to the one found in other market settings, performs better in explaining investors' trading behaviour with regard to price clustering. For the LSE, Board et al. (2000) argue that "fair weather market making" (the tendency of market makers to fulfil their contractual obligations at favourable market conditions only, hence avoiding taking excessive risks) is closely related to price clustering at round pennies. In particular, Board et al. (2000) show that 97.5% of quotes are priced at round pennies.

A second stream of literature is generally consistent with the view that market makers operating at an upstairs market are able to screen on the degree of information held by counterparties, hence informed traders are deterred from trading at the upstairs market (see Bessembinder and Venkataraman, 2004 and Smith et al., 2001). Research on informed trading in parallel markets also confirms the hypothesis that the degree of trader anonymity is associated with more informed trading (Grammig et al., 2001). Both streams of literature imply that liquidity traders have an incentive to trade at the upstairs market (see Easley and O'Hara, 1987). Also, Rhodes-Kropf (2005) argues that while market makers may offer better prices to their clients as a means of attracting liquidity, a second reason for price improvement may come from the customers' bargaining power over market makers.

Given these findings in the literature, we hypothesise that in a setting where the minimum tick size is applied to the order book but not for the upstairs market (SETS at the LSE), participants anchor their prices to the established minimum tick size applied at the downstairs market. We further investigate whether this anchoring effect is justified by differences in the effective half spread, a transaction costs measure, or by information asymmetries.

We show that the presence of a minimum tick size in the order book but not at the upstairs market implies the existence of price barriers in the upstairs market in a way similar to the existence of other asset price barriers (see Donaldson and Kim, 1993). The tendency of investors to perceive specific prices as support or resistance levels leads to price clustering above and below such prices, a finding which is very similar to the "reverse clustering" theory (see Bagnoli et al., 2006, Bhattacharya et al., 2012 and Johnson et al., 2008). The latter refers to the tendency of investors to "anchor" their prices around final digits 0 and 5 (Bhattacharya et al., 2012), hence round numbers operate as barrier and resistance levels (Bagnoli et al., 2006). However, our study differs from the above in several respects. First, we show that traders at the upstairs market anchor their prices to the notional minimum tick size. Second, we document the economic significance of this practice. Third, we show the economic relationship between reverse clustering and trade size. Finally, we are able to study these effects separately for liquidity providers and liquidity demanders.

To the best of our knowledge, this is the first paper which shows that market makers employ "cluster undercutting" practices on the basis of a notional minimum price increment. We report that liquidity providers consistently buy just below the implicit minimum price increment and consistently sell just above it. We refer to this as the "price anchoring" effect. The probability of buying just below the tick or selling just above it is strongly related to stock-price momentum and periods of increased trade intensity. Overall, this decision of market makers is only partly explained by differences in informed trading and is more related to the notional price barriers and resistance levels introduced by the minimum tick size of the order book. Our results are consistent with the findings by Board and Sutcliffe (2000) that market makers charge more for customer buys than customer sells. We refer to this as the "price adjustment" effect. Importantly, we show how this process is facilitated in the upstairs market via the notional minimum tick.

The remainder of this paper is organised as follows. Section 2 discusses the previous literature, and the hypothesis development. Section 3 explains the data selection and methodology. Section 4 presents the results and Section 5 concludes the paper.

2. LITERATURE REVIEW AND HYPOTHESES

A key question that arises with regard to the interaction between the order book and the upstairs market relates to the preferred trading platform for informed traders. Previous literature has consistently reported that market makers at an upstairs market reduce adverse selection costs (the component of transaction costs that is associated with trading with informed clients) by screening potential counterparties. Seppi (1990) reports that the lack of trader anonymity is a key factor in allowing market makers in such a setting to identify informed traders and describes mechanisms used by market makers to minimise adverse selection costs. Barclay and Warner (1993), Bessembinder and Venkataraman (2004), Booth et al. (2002), Hansch et al. (1998), Madhavan and Cheng (1997) and Smith et al. (2001) verify the finding that informed traders are discouraged from trading at an upstairs market. Bessembinder and Venkataraman (2004) also report that upstairs trades contain less information than downstairs trades despite being larger.

Seppi (1990) suggests that informed traders are reluctant to negotiate prices at an upstairs market as this reveals their identity and creates an implicit contract for future transactions. Hence, only uninformed traders are inclined to negotiate prices and gain price improvement. On the other hand, Rhodes-Kropf (2005) argues that price improvements may also reflect customers' increased bargaining power, a hypothesis that deviates from Seppi's (1990) informed-trading assumption. It is found that large trade size is positively associated with negotiation power. Price improvements are also greater for dealers with better negotiation skills and lower discount rates.

Harris (1991) identifies that price and time priority rules are not relevant in dealer markets (and the LSE upstairs market is no exception). However, while tick rules are determined endogenously in order to facilitate price and time priority in limit order markets, hybrid markets may lead to execution priority for certain market participants. Portniaguina et al. (2006) find that a reduction in the tick size increases the probability of specialists stepping ahead of clients in the limit order book. However, as noted by Huang and Stoll (2001), without a tick rule, customers may also potentially step ahead of dealers as all market participants are equally affected.

Harris and Lightfoot (2004) show that NASDAQ trading is characterized by “subpenny jumping”, the practice of using the subpennies 1 and 9 to step ahead of existing quotes. The latter is closely linked to the “reverse” price clustering hypothesis. Bhattacharya et al. (2012) report that studies on financial markets have underestimated (overestimated) the significance of the final digits 1 and 9 (0 and 5) and that a “reverse clustering”, similar to that found in other market settings (e.g. consumer), performs better in explaining investors’ trading behaviour. Also, Bagnoli et al. (2006) show that trades below (above) final digits of 0 are followed by net selling (buying).[2] Bagnoli et al. (2006) also report that a left-digit truncation effect, the tendency of investors to round prices at the leftmost digit, is not supported by their data. Instead, it is argued that round numbers operate as barrier and resistance levels, similar to the findings of Donaldson and Kim (1993). The latter study documents investors’ sentiment to prices falling (increasing) below (above) a support (resistance) level. Their findings show that prices exhibit a negative (positive) jump, following the breakthrough of a support (resistance) level.

[2] See also Johnson et al. (2008).

Based on Portniaguina et al. (2006) and Bhattacharya et al. (2012), we hypothesize that in a setting like SETS at the LSE, in which the minimum tick size is applied for the order book but not for the upstairs market, participants anchor their prices to the established minimum tick size applied in the downstairs market. That is, given the findings reported in Verousis and ap Gwilym (2013) that the upstairs market operates on the basis of a notional minimum tick size, we hypothesize that market participants will resort to "penny jumping" strategies on the basis of that notional minimum tick size.[3] However, this hypothesis is not similar to "subpenny pricing" as the latter implies trading practices for gaining execution priority over existing quotes, whereas our hypothesis implies that prices are used as anchor levels in the upstairs market where there is no order book. We refer to this hypothesis as the "price anchoring effect". In their seminal work on the anchoring-and-adjustment heuristic, Tversky and Kahneman (1974) refer to individuals assessing subjective probability distributions when making decisions and adjusting their final actions according to their original beliefs for that distribution. In their example on predicting the Dow Jones index value, the authors note that the subjects may "... state overly narrow confidence intervals which reflect more certainty than is justified by their knowledge about their assessed quantities" (Tversky and Kahneman, 1974, p. 1129). We hypothesize that it is possible to predict the direction of the relationship between a notional tick size in the upstairs market and an established tick size in the downstairs market in a fashion similar to anchoring-and-adjustment heuristics. That is, in line with the findings of Portniaguina et al. (2006), if a reverse clustering effect is present in the data, then buy and sell orders will not cluster uniformly around anchor prices but the findings should adhere to the price efficiency gained from this practice. In particular, it is reasonable to assume that traders will buy below the notional minimum tick and sell above it. Finally, it is reasonable to assume

[3] "Quote matching" or "penny jumping" strategies are described in Harris (2002).

that investors trading at the upstairs market may time their trades based on two criteria: firstly, the information content of trades (Seppi, 1990) and secondly, the economic cost hypothesis i.e. extract larger profits by trading at specific prices (Rhodes-Kropf, 2005). We refer to this hypothesis as the "adjustment effect".

3. DATA AND METHODS

The data used in this study are sourced from the LSE historical data service and include all trades reported on the exchange during 2005.[4] The database identifies off-book ("ordinary", market maker, MM) trades, which in contrast with the order-book trades, are not required to adhere to the minimum price increment restrictions. All cancelled, zero-volume, zero-price and out-of-hours trades are removed from the dataset. In order to detect outliers, we delete all trades that report a price change between previous prices or the present midquote greater than 25% (see Bessembinder, 1997). We also avoid stale pricing and missing data problems by selecting firms that report at least one trade per hour for the trading period. This criterion also filters out the smallest capitalisation stocks that are otherwise eligible. 92 firms are selected, of which 57 (62%) trade (in the order book) at a minimum tick size of xx.25p and 35 (38%) trade (in the order book) at a minimum tick size of xx.50p.[5] Overall, for our sample, approximately 14% of

[4] SETS was created in 1997 and is the main trading platform for the blue chip stocks trading on the LSE. SETSmm (see the next footnote) was introduced in 2003. The LSE operates under the same structure since then (see also Carollo et al., 2012 and Chelley-Steeley and Skvortsov, 2010).

[5] The criteria lead to 93 firms being selected. However, one firm is trading on SETSmm for small firms. The important difference between SETS and SETSmm is that in the latter, market makers are allowed to enhance the depth of the order-book by posting quotes. SEAQ (Stock Exchange Automated Quotation System) is another system in which market makers are also obliged to quote prices on the electronic display system. The proportion of firms selected in the sample is approximately 43% of the 213 firms traded at the upstairs market in 2005. The

trades are conducted at the upstairs market, which however represent approximately 44% of the total trading volume traded across both venues.

We employ the tick trade identification algorithm in order to classify trades (see Finucane, 2000). Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells.[6] For the upstairs market, LSE Rule 3012.2 instructs market makers to report trades when dealing with investors (i.e. non exchange members).[7] Hence for the upstairs market, it is appropriate to assume that investors are always the trade initiators, thus trades that are classified as buys are effectively buy orders

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92 firms are responsible for approximately 61% of the total number of trades executed at the upstairs market in 2005 (approximately 6.68 million trades in total).

[6] The use of the most recent trade is justified by the selection of the most liquid assets (the average inter-trade duration is less than 5 minutes). However, we also conduct a robustness check by selecting a smaller sample of the 17 most liquid stocks and repeating the analysis. This gives similar results. Also, we calculate spread measures in order to identify the effect of duration and the results are also generally consistent with the overall findings. As a final test, we use the midquote rather than previous trade to classify trades, however, more than 70% of trades are classified as buys using this approach, which is implausible. The trade classification algorithm is preferred over the Lee and Ready quote classification algorithm. While the latter performs well in an electronic order book, the nature of our data makes the process of matching quote and trade data very difficult (see also Footnote 12). Chakrabarty et al. (2012) show that the Lee and Ready algorithm performs poorly when trade data are not correctly merged with quotes.

[7] Trades conducted between two market makers are discarded from the sample (they represent less than 1% of the total). Hence, in this paper, all trades conducted at the upstairs market are between a market maker and an individual investor. 'Individual' refers to a party trading on behalf of an institutional investor.

from the perspective of the liquidity provider (the market makers).[8] In order to study trade pricing from the perspective of the market makers, we maintain the original trade classification. We use binomial z-tests for the equality of proportions 'below' and 'above' multiples of the minimum tick size. 'Below' refers to trades executed at prices up to 5 decimal points below a multiple of the tick size (e.g. price ending in .45 for the 0.5 tick size). Similarly, 'above' refers to trades conducted at decimal prices that are up to 5 decimal digits above the multiples of the tick size (e.g. price ending in .55 for the 0.5 tick size). We construct variables that capture the total number of trades conducted within these thresholds above and below the minimum tick size. In order to control for trade size differences, we estimate the z-test for 'small', 'medium' and 'large' trades[9] and also perform separate tests for buy and sell orders.[10]

The following steps are taken in order to test the hypothesis that the institutional setting and the absence of minimum tick size regulations offer scope to some market participants to extract large economic rents. First, we employ a probit model with marginal effects and robust standard errors in order to investigate the effect of the notional tick size on the pricing for small, medium and large trades. The binary dependent variable equals 1 if the trade is classified as a buy and 0 if a sell. We employ eight dummy variables: $D_{1,s}$ equals 1 for trades executed at the leftmost decimal digits 1-5 and zero otherwise. Equally, we do the same for the remaining seven "price anchors". $D_{2,s}$ equals 1 for trades executed at the leftmost decimal digits 20-24

[8] Hence, in the first stage of this procedure, the tick trade algorithm is employed to classify trades as buyer or seller initiated and in the second stage Rule 3012.2 is employed to classify trades from the perspective of the liquidity provider.

[9] 'Small' and 'large' refer to trades conducted at the smallest and biggest trade size quartiles, respectively. 'Medium' trades refer to trade sizes that are between the 25th and 75th percentile.

[10] The upstairs market has been praised for the facilitation of large orders and there is a substantial difference in mean trade sizes of orders conducted at the upstairs market versus the order book (see Bessembinder and Venkataraman, 2004). Hence, the classification of trades as 'small' does not imply that these are retail trades.

and zero otherwise, $D_{3,s}$: 26-30, $D_{4,s}$: 45-49, $D_{5,s}$: 51-55, $D_{6,s}$: 70-74, $D_{7,s}$: 76-80, $D_{8,s}$: 95-99. The subscript *s* is used to denote assets that trade under the minimum tick of 0.25. The intention with this approach is that the dummy variables will capture any imbalances between buy and sell orders around the hypothesized "price anchors". We control for differences between small and large trade sizes by adding a dummy variable for trade size (TS) which is allowed to interact with the price threshold barriers above. The regression is summarised below:

$$TD_{i,t} = a_1 + \sum_{j=1}^{8} \beta_j TS_1 * D_{j,s} + \sum_{j=1}^{8} \gamma_j TS_2 * D_{j,s} + \sum_{j=1}^{8} \delta_j TS_3 * D_{j,s} + \varepsilon_{i,t} \qquad (1)$$

Where *TD* is the trade direction binary dummy recorded at time *t* for each firm *i*. $D_{1,s}$ to $D_{8,s}$ are the dummy variables outlined above. TS_1, TS_2 and TS_3 are control dummies for small-, medium- and large-sized trades respectively. Positive signs are expected for $D_{2,s}$, $D_{4,s}$, $D_{6,s}$ and $D_{8,s}$, reflecting excess buy orders from market makers, and negative signs are expected for $D_{1,s}$, $D_{3,s}$, $D_{5,s}$ and $D_{7,s}$, reflecting excess sell orders.

The above specification is applied for the 57 assets that trade under a minimum tick of 0.25. For the remaining assets, although the minimum tick size is 0.50, we also estimate Equation (1). If an anchoring effect exists, then we should observe clustering around the multiples of the minimum tick and also observe less clustering around the multiples of the smaller tick.

Second, we examine the conditions that affect the choice of trading below or above the multiples of the notional minimum tick size. We estimate a regression model based on a binary dependent variable for trades above or below the minimum tick size. Since the decision to buy or sell is taken before the decision to trade below or above the minimum tick, we run separate regressions for sell and buy trades. We employ the following probit model:

$$DD_{i,t} = a_1 + \beta_1 QS_{i,t} + \beta_2 Vol_{i,t} + \beta_3 Mom_{i,t} + \beta_4 OD_t + \beta_5 CD_t + \beta_6 TS_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where DD is the binary direction dummy variable that takes the value of one for trades conducted at prices within the threshold above the multiples of the minimum tick and zero for trades at prices within the threshold below the tick points. $QS_{i,t}$ is the quoted spread measured as the difference between the ask and bid prices prior to any trade divided by two.[11] Volatility ($Vol_{i,t}$) is calculated as the absolute value of the stock return over the previous 30 minutes (see Barclay et al., 2003). $Mom_{i,t}$ is a momentum indicator variable that is calculated as the average stock return over the previous 30 minutes times one for buy orders or times negative one for sell orders. OD_t and CD_t are opening and close dummies measured over the first and last 30 minutes of trading respectively. $TS_{i,t}$ refers to the natural logarithm of trade size.[12]

Third, we assess the economic significance of the results by employing the effective half-spread measure, which is a consistent transaction costs' measure that also accounts for trading inside the quotes. The effective half-spread which gives the cost of trading for a single trip trade is calculated as follows (Bessembinder and Kaufman, 1997):

$$Effective\ half-spread_{i,t} = 100D_{i,t}(P_{i,t} - M_{i,t})/M_{i,t} \tag{3}$$

where $D_{i,t}$ equals one for buy trades and negative one for sell orders. $P_{i,t}$ is the trade price and $M_{i,t}$ is the midpoint that prevailed at the time of the trade.

[11] The quoted spread is calculated by using quotes that are submitted at least three minutes prior to the trade (see also footnote 12).

[12] Robust standard errors are reported.

As LSE rules allow market makers to report trades within three minutes of their execution, we calculate the effective half-spread by selecting the most recent quotes that have been posted at least three minutes before the trade but not more than 60 minutes old.[13]

Bessembinder (1997) identifies that the effective half-spread may give inconclusive results when market makers widen spreads as a reaction to a perception of trading with a privately informed counterparty. In order to assess this possibility, we decompose the effective half-spread into its information-based component and the market revenue component. We measure price impact, the component of the spread that accounts for superior information, as follows:

$$Price\ impact_{i,t} = 100D_{i,t}(M_{i,t+5} - M_{i,t})/M_{i,t} \tag{4}$$

Similar to Alexander and Peterson (2007), we measure price impact as the difference in quote midpoints between the current trade and the next trade reported at least 5 but not more than 60 minutes later. $M_{i,t}$ still denotes the midpoint posted at least three minutes, and not more than 60 minutes, prior to the trade.

Finally, we measure the realised spread component as the difference between the effective half spread and the price impact component. The realised half-spread is a suitable measure of market making revenues as it is net of losses to informed traders (see Bessembinder, 1997).

[13] It is clear that in this market setting, the calculation of the spread is only an approximation and should be treated with caution. In order to test the robustness of this method, we also calculate spreads using quotes that are submitted 20 seconds prior to the trade and are not more than 60 minutes old (see Bessembinder and Kaufman, 1997), which produces qualitatively very similar results (not presented but available upon request).

4. RESULTS

Table 1 provides the descriptive statistics of the dataset. The total number of observations is 4,104,510, 63% (37%) of which refer to assets trading under a notional tick of 0.25p (0.50p). The average trade prices for the assets trading at xx.25p are 313.39p and 312.71p for buy orders and sell orders respectively. The average trade prices for assets with the xx.50p tick size are 760.63p and 764.54p for buy and sell orders respectively. The average trade size for assets trading at xx.25 is larger than the average trade size for assets trading at xx.50. Multiplying average price by average size produces very similar transaction sizes across the four categories. The effective half-spread ranges are 4.2 to 5.6 basis points for buy orders and 3.4 to 2.4 basis points for sell orders. These buy and sell spread differences are statistically significant, as are the differences in the price impact estimates between buy and sell orders. In absolute terms, for both tick sizes, the price impact of sell orders is greater than that of buy orders.[14] Finally, for both ticks, average execution costs (net of price impact) are higher for sells, which partially reflects the higher costs that liquidity traders have to pay when there is insufficient liquidity in the order book (see also Friederich and Payne, 2007).

Insert Table 1 about here

Before investigating whether market makers' actions imply a price-anchoring-and-adjustment effect, we need to establish that the price resolution in the upstairs market is directly related to the minimum tick size that applies at the order book. Market makers trade using up to four decimal digits, while the tick size restrictions applied to order-book trades require investors to submit prices that are multiples of the minimum tick size. Hence, a question arises regarding

[14] As expected, the sign for the average price impact measure is positive for buys and negative for sells.

the optimal price resolution and in particular about the interaction of market maker trades with the minimum price increment. Table 2 presents the distribution of the price multiples that adhere to the order-book minimum tick size as a percentage of the total number of trades. Results for both buy and sell orders show that price clustering occurs on the multiples of tick size and increases as trade size increases. Hence, there is a clear association between the order-book minimum tick and the pricing of off-book trades. This effect is well documented in the price clustering literature (see Harris, 1991 and Chung et al., 2004).

Insert Table 2 about here

In order to study the potential impact of the minimum tick size on off-book trades, we focus only on the two leftmost decimals. Figure 1 plots the distribution of the buy-to-sell ratio for small, medium and large trades. Panel A refers to the distribution for assets trading at the notional tick of xx.25 and Panel B refers to the distribution for assets trading at the larger notional (xx.50) minimum tick. There is a distinctive pattern in the frequency ratio of buy to sell orders for off-book trades.[15] In particular, it becomes clear that for small trades, buy orders tend to cluster below the multiples of the minimum tick size and sell orders cluster on and above the minimum tick multiples.

Recall that we have set out two explicit hypotheses: the first is that market participants at the upstairs market will anchor their prices to the established minimum tick size applied in the downstairs market. That is, we expect to see a concentration of orders around multiples of the notional minimum tick size. Secondly, we hypothesise that it is possible to predict the direction of the relationship between the notional tick size in the upstairs market and an established tick

[15] The expected value for the ratio is one (buys equal sell orders).

size in the downstairs market. The combination of the two hypotheses implies that in Figure 1 we should observe more buy orders below the notional minimum tick size and more sell orders above it. Looking at each multiple of the notional minimum tick size in isolation, for example the distribution of the buy-to-sell ratio around the tick threshold of xx.25, then a local maximum (minimum) refers to the observation where the buy-to-sell frequency ratio is at its maximum (minimum) level. The null hypothesis is that, under a uniform distribution, the buy-to-sell ratio will remain constant across all price levels. For the smaller tick size, local maxima appear at the prices of xx.22, xx.44, xx.69 and xx.94. Also, local minima appear on xx.00, xx.25, xx.50 and xx.75. For medium sized trades, the same pattern, albeit less distinctive also applies; there is a concentration of buy (sell) orders below (above) the notional tick size multiples.[16] Finally, for large trades, although the ratio distribution is more balanced, local maxima appear on xx.17, xx.43, xx.68 and xx.93. Local minima are found on xx.25, xx.50, xx.79 and xx.98.

Insert Figure 1 about here

Panel B of Figure 1 shows a similar pattern around the multiples of the minimum tick. Hence, for small trades, local maxima can be found on xx.38 and xx.93 and local minima at xx.02 and xx.51. For medium-sized trades, local maxima are found at xx.48 and xx.98 and local minima at xx.51 and xx.01. Finally, for large trades, the distribution is more even, while local maxima are located on xx.04 and xx.52 and local minima on xx.98 and xx.56.

The above findings reveal that the distribution is largely focused around the multiples of the notional minimum tick size and is a function of trade size. Viewing this finding from the perspective of the market maker, it reveals that liquidity providers consistently buy below the

[16] Bagnoli et al. (2006) show that price observations below (above) a threshold are followed by net selling (buying).

implicit minimum price increment and consistently sell above it. This result is stronger for the smaller trades and tends to diminish as trade size increases. Nevertheless, taking into account that costs increase as size increases, a clear association between market makers' pricing policy and price clustering arises for all three size categories.

We further investigate this finding in Table 3. This presents the z-test estimates for the equality of proportions above and below the multiples of the minimum tick size for buy and sell orders across small, medium and large orders. It is clear that statistically significant differences exist in the frequency of trades conducted above and below the minimum price increments.[17] This is true even when controlling for trade size differences (see also Bagnoli et al., 2006).

Insert Table 3 about here

While the above findings demonstrate the concentration of trading below and above the price multiples for buy and sell orders respectively, a question arises with regard to the distribution of volume. If the frequency ratio is an artefact of specific events, the volume figure will be evenly distributed along the available price set. We plot the distribution of the buy-to-sell volume ratio in Figure 2.

Insert Figure 2 about here

For the xx.25 tick size, Panel A of Figure 2 shows that for small trades, the distribution closely follows the frequency ratio (correlation of 0.99). A similar relationship is also present for medium sized trades, hence trades that are concentrated at the first three volume quartiles

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[17] The z-tests for each individual asset report similar findings (results not presented).

exhibit the same properties around the minimum tick price. However, for large trades, a reversed relationship is observed. In particular, local maxima are now observed on xx.08, xx.18, xx.52 and xx.77, and local minima on xx.24, xx.41, xx.74, and xx.89. Also, the correlation coefficient between frequency and volume is negative but not statistically significant.

Panel B of Figure 2 shows the distribution of the volume buy-to-sell ratio for the larger tick size. For small trades, the distribution of volume also follows the frequency distribution, hence local maxima are found on xx.41 and xx.98 and local minima on xx.51 and xx.02. Similarly, for medium-sized trades, the local maxima and minima are found on xx.48, xx.98 and xx.01, xx.51 respectively. The distribution of the volume ratio for large trades is negatively correlated with the frequency distribution and local maxima (minima) are found on xx.49 and xx.99 (xx.59 and xx.91). Table 3 presents the t-test results for the equality of mean volumes between trades conducted above and below the multiples of the minimum tick size for buy and sell orders, showing statistically significant differences. The latter finding is only challenged for the large buy orders.

Overall, the above findings suggest that trading at the upstairs market mirrors the multiples of the minimum tick price and when viewed from the perspective of the market makers, it seems that they can step-ahead of this implicit price by quoting at more favourable prices for themselves. This result is highly significant for small and medium-sized trades and tends to disappear for large trade sizes but not for higher transaction frequencies.[18]

[18] A direct investigation of the price that applied at the time when market maker trades were conducted is not feasible because market makers have a 3-minute window to report their trades. However, the fact that the spread is calculated within a small time interval and that (especially for the smaller tick) the assets included in the sample are highly liquid, leads us to believe that the midquote and the asset price used to calculate the effective half spread differ by a maximum of one or two ticks.

Insert Table 4 about here

Having established that both the price-anchoring and the adjustment effect are present in the data, our next step is to quantify the extent to which market makers are likely to trade below and above the notional minimum tick size. According to the price-anchoring effect, trading will systematically occur around the notional minimum price multiples. According to the adjustment effect, market makers will systematically buy below the notional price multiples and sell above them. Tables 4 and 5 present the probit regression results for the trade indicator variable. Table 4 is based on the 0.25 tick size. For small and medium sized trades, all dummy variables are highly significant and have the anticipated sign. Trading around the four tick thresholds (xx.00, xx.25, xx.50 and xx.75) shows that market makers consistently buy below the threshold price and sell above it. In particular, when trades are conducted below (above) the minimum tick, the probability of the trade being a buy (sell) increases by between 7 (4) and 9 (7) percent. Finally, the results for large trades show that market makers will tend to buy below the multiple price increments (correct signs when positive sign anticipated), yet, selling above the minimum price is significant for only 1 of 4 dummies.

In a similar probit model for the larger notional tick size, Table 5 also shows consistent and highly significant buying (selling) activity below (above) the multiples of the minimum tick size for small and medium sized trades (and similar magnitudes of marginal effects). In line with our hypothesis, while clustering at the notional minimum tick of xx.25 is also present, the marginal effects analysis shows that trading around multiples of the notional minimum tick of xx.50 is much more probable and follows the anticipated sign.

Insert Table 5 about here

We confirm that tick size restrictions that apply only in the order book have an explicit effect on the pricing of assets traded at the upstairs market. This finding holds for both tick sizes. Accordingly, Tables 4 and 5 show that multiples of the notional tick size act as focus levels and market participants price their assets according to these levels.[19] It is also worth noting that the results reported in Tables 4 and 5 confirm the hypothesis that the reverse clustering pattern observed for the LSE upstairs market may ultimately be the outcome of a bargaining game between market participants, however the platform upon which the bargaining game is executed is not uniform. That is, negotiations occur on the basis of the notional price increment and not on a finer grid.

However, before identifying the economic significance of the above trading pattern, Table 6 investigates the conditions that prevail in the market at the time of the trade. The results on the quoted spread for both tick sizes show that the decision to trade above or below the multiples of the minimum tick is taken irrespective of whether the spread is narrow or wide (a result which holds for both buy and sell orders). For the remaining variables, Panel A of Table 6 shows that the probability of observing a buy (sell) order conducted below (above) the minimum tick decreases with short-term volatility and increases with return momentum. The stock-price momentum variable reveals that the probability of buying below the tick or selling above it increases by 22% and 27% when a positive short-term momentum exists, for buy and sell orders respectively. During periods of increased trade intensity like the market open, the probability to observe buy orders below the minimum tick increases by 14%, whereas the

[19] The price levels we investigate are different than the threshold levels discovered in previous studies (see Donaldson and Kim, 1993) as the latter refer to a linear interpretation of the price level (i.e. pricing changes when a level is exceeded) while our results are concerned with the pricing around a threshold level.

probability to observe sell orders above the tick decreases by 13%.[20] A less pronounced effect is observed for sell orders at the market close. Finally, the change in the probability of buying or selling below the tick ranges from 4 to 5% for increases in the trade size, which confirms previous findings that the distribution of prices is altered for the larger trades. The results in Panel B of Table 6 confirm the direction of the relationships found in Panel A. Hence, as in Panel A, return momentum and short-term volatility have the largest effect on the decisions of market makers to anchor their trades to the implicit tick size.

Insert Table 6 about here

Finally, we focus on the economic impact of our findings. We investigate whether the practices of market makers (to buy below the minimum tick and sell above it) are justified by the presence of informed trading or are economically justifiable. Panel A of Table 7 studies the effective half spread around the minimum price increments. Panel B calculates the price impact estimates and Panel C presents the spread net of transaction costs. The results on the effective half-spread measure indicate that buy orders for the smaller tick assets trade on average around 6 basis points higher when trading below the implicit minimum tick than when trading above it. This result is consistent across trade sizes. For the larger tick, the same directional relationship is reported for small and medium-size trades albeit the difference is significant for the smaller trades. For large trades, no statistically significant difference is found. In contrast, sell orders submitted above the minimum price for the lower tick stocks are executed on average around 6 basis points higher than the orders submitted below the minimum price increment. This result holds for both minimum tick sizes. These findings show that investors

[20] We also investigated duration as a measure of trade intensity. The results were consistent for buy orders however remained insignificant for sells.

may tend to anchor prices around the multiples of the minimum tick size when trading in the upstairs market.[21]

Insert Table 7 about here

Panel B of Table 7 investigates whether these differences between trades conducted above and below the minimum tick are related to trading activity and/or reflect adverse selection costs faced by market makers. Generally the results are mainly significant for the buy orders under the smaller tick size, however, both the magnitude and the direction of the relationship of the price impact estimates for trades submitted below and above the tick, show that informed trading differences are of importance to the findings. Also, for the larger tick size, this relationship is more obviously of little significance. Panel C of Table 7 documents the transaction costs faced by investors net of the adverse selection costs. The decision to trade below or above the minimum tick is not taken on the basis of information asymmetries, and the costs arising from the trading pattern are only attributable to market makers' pricing practices (the results are mostly highly significant and consistent across both ticks). The results on the realised spread component of trades clearly show that buy orders below the tick tend to be costlier to market makers than buy orders above it. This result is consistent for both ticks and is significant for 5 of 6 cases. For sells, the opposite relationship is highly significant for 4 of 6 cases, hence sell orders conducted above the tick are more expensive than sell orders conducted below it.

[21] It should be mentioned though that this relationship does not imply that investors are better off when submitting orders at the upstairs market as we are only able to show that a behavioural threshold exists in the market that allows market makers to use it when trading upstairs.

5. CONCLUSIONS

Price clustering refers to the tendency of investors to concentrate their terms of trading in a specific set of prices. It has been widely documented and several rational explanations have been proposed which are consistent with the evidence. A "reverse clustering" theory has recently emerged which attempts to explain clustering as the tendency of investors to trade around focal numbers rather than on focal numbers (see Bhattacharya et al., 2012). We link this theory to the "anchoring-and-adjustment" heuristic bias documented by Tversky and Kahneman (1974), and apply this perspective to the setting of the London Stock Exchange.

Specifically, we hypothesize that the implicit interaction between the upstairs and the downstairs market alters the pricing mechanism at the upstairs market. Hence, the probability distribution of prices quoted/traded at the upstairs market is heavily influenced by the minimum tick size rules that apply in the order-book market but are not obligatory when trading at the upstairs market. We refer to this hypothesis as the "price anchoring effect". We report that liquidity providers consistently buy below the implicit minimum price increment and consistently sell above it. The probability of buying below the tick or selling above it is strongly related to stock-price momentum and periods of increased trade intensity. Thus, we confirm the hypothesis that the institutional setting and the absence of minimum tick size regulations offer scope to market participants to use the implicit minimum tick as a threshold price in the upstairs market.

We also study the economic significance of clustered trades at the upstairs market, firstly using transaction cost measures in order to measure the ex-ante cost of trading, and secondly using price impact measures for the ex-post profit implications of trades. We hypothesise that investors trading at the upstairs market may time their trades based on two criteria: the information content of trades and the economic rents that can be extracted by the trade. We refer to this hypothesis as the "adjustment effect". We report that market participants trading at the upstairs market receive better execution costs when selling below the tick and buying above it. This decision of market makers is only partly explained by differences in informed trading and is more related to the notional price barriers and resistance levels introduced by the minimum tick size of the order book.

Overall, our results show that “cluster undercutting” (see Bhattacharya et al., 2012) has important implications for the design of the upstairs market at the LSE. Previous studies have focused on the tendency of market participants to reduce their terms of trading in a popular set of numbers only. This study offers insights on the trading practices of liquidity suppliers, whereby market makers take advantage of the institutional setting to step ahead of others. The results should be of interest to market participants at the LSE.

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Table 1: Descriptive statistics

Notional Tick Size	xx.25		xx.50	
	Buy orders	**Sell orders**	**Buy orders**	**Sell orders**
N	1,240,344	1,332,107	748,282	783,777
(%)	(48.21)	(51.79)	(48.84)	(51.16)
Average price	313.39	312.71	760.63	764.54
Average size of trades	43,375.28	39,935.07	19,895.28	16,629.73
Effective half spread	0.056	0.034***	0.042	0.024***
Price impact	0.014	-0.029***	0.008	-0.030***
Realised spread	-0.042	0.063***	0.034	0.054***

Notional tick size refers to the distribution of the price multiples that would adhere to the minimum tick size. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider e.g. trades that are classified as buys are effectively buy orders from the perspective of the market makers. N refers to the total number of trades. In parentheses, the percentage of the total number of trades at each category. Average price and average size refer to the weighted average price and size per stock in the sample, respectively. The effective half-spread is calculated as the difference between the observed price and the midquote prior to the trade, standardised by the midquote price. For the calculation of the effective half-spread in the upstairs market, we use midquotes that are posted at least 3 minutes before the trade (a maximum of 60 minutes). Price impact refers to the difference in quote midpoints between the current trade and trades reported at least 5 minutes after the announcement of the trade (a maximum of 60 minutes). The realised spread refers to the difference between the effective half-spread and price impact measures. T-tests for the pairwise equality of means are reported. **, * significant at the 5% and 1% level respectively.**

Table 2: Notional distribution of final digits at the upstairs market

Panel A: xx.25

	Buy orders			Sell orders		
	Small	**Medium**	**Large**	**Small**	**Medium**	**Large**
xx.00	0.47	2.04	4.86	0.84	2.62	4.87
xx.25	0.32	1.21	2.25	0.60	1.76	2.55
xx.50	0.40	1.70	3.34	0.77	2.40	3.64
xx.75	0.31	1.27	2.36	0.59	1.73	2.53
Total	1.52	6.22	12.81	2.80	8.52	13.59

Panel B: xx.50

xx.00	2.07	5.06	6.37	2.71	5.49	6.38
xx.50	1.51	3.57	3.39	2.06	4.29	3.57
Total	3.58	8.63	9.76	4.77	9.78	9.95

Panels A and B present the distribution of the price multiples that would adhere to the minimum tick size as a percentage of the total number of trades. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider e.g. trades that are classified as buys are effectively buy orders from the perspective of the market makers. N refers to the total number of trades. Small and large refer to trades conducted at the smallest and biggest trade size quartiles, respectively. Medium trades refer to trade sizes that are between the 25th and 75th percentile. Total refers to the total percentage of trades executed at the above ending decimals.

Table 3: Z-test and t-test estimates for thresholds below versus above tick size multiples

	Buy orders			Sell orders		
	Small	**Medium**	**Large**	**Small**	**Medium**	**Large**
Frequency	-193.88***	-245.31***	-119.09***	-282.67***	-356.87***	-140.57***
Volume	33.66***	-31.94***	0.01	25.37***	-35.06***	13.99***

This table presents binomial z-tests for the equality of proportions below and above multiples of the minimum tick size. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider (the market makers). N refers to the total number of trades. Small and large refer to trades conducted at the smallest and biggest trade size quartiles, respectively. Medium trades refer to trade sizes that are between the 25th and 75th percentile. Frequency refers to the estimated z-test figure for small, medium and large trades. Volume refers to the difference in the average volume estimates between trades conducted above and below the multiples of the notional minimum tick size. T-tests for the equality of means are reported. * significant at the 1% level.**

Table 4: Probit regression estimates with marginal effects and robust SE (Tick: xx.25)

Trade Size	Tick Threshold dummies (range)	Expected Sign	Coefficient	Marginal Effects
Small	D_1 (1-5)	-	-0.10***	-0.04
	D_2 (20-24)	+	0.22***	0.09
	D_3 (26-30)	-	-0.16***	-0.06
	D_4 (45-49)	+	0.23***	0.09
	D_5 (51-55)	-	-0.10***	-0.04
	D_6 (70-74)	+	0.23***	0.09
	D_7 (76-80)	-	-0.18***	-0.07
	D_8 (95-99)	+	0.17***	0.07
Medium	D_1 (1-5)	-	-0.03***	-0.01
	D_2 (20-24)	+	0.24***	0.10
	D_3 (26-30)	-	-0.11***	-0.04
	D_4 (45-49)	+	0.22***	0.09
	D_5 (51-55)	-	-0.09***	-0.04
	D_6 (70-74)	+	0.22***	0.09
	D_7 (76-80)	-	-0.14***	-0.06
	D_8 (95-99)	+	0.17***	0.07
Large	D_1 (1-5)	-	0.05***	<-0.01
	D_2 (20-24)	+	0.14***	0.06
	D_3 (26-30)	-	<-0.01	<-0.01
	D_4 (45-49)	+	0.10***	0.04
	D_5 (51-55)	-	0.01	<-0.01
	D_6 (70-74)	+	0.14***	0.06
	D_7 (76-80)	-	-0.04***	-0.02
	D_8 (95-99)	+	0.07***	0.03

The dependent variable is a trade direction binary dummy that equals 1 is the trade is classified as a buy and 0 if it is classified as a sell. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider (the market makers). N refers to the total number of trades. Small and large refer to trades conducted at the smallest and biggest trade size quartiles, respectively. Medium trades refer to trade sizes that are between the 25th and 75th percentile. D_1 equals 1 for trades executed at the leftmost decimal digits 1-5, D_2 for 20-24, D_3: 26-30, D_4: 45-49, D_5: 51-55, D_6: 70-74, D_7: 76-80, D_8: 95-99. The subscript s that refers to assets trading under the minimum tick of 0.25 is dropped from this table. * significant at the 1% level.**

Table 5: Probit regression estimates with marginal effects and robust SE (Tick: xx.50)

Trade Size	Tick Threshold dummies (range)	Expected Sign	Coefficient	Marginal Effects
Small	D_1 (1-5)	-	-0.19***	-0.07
	D_2 (20-24)	+	-0.04***	-0.02
	D_3 (26-30)	-	-0.10***	-0.04
	D_4 (45-49)	+	0.26***	0.10
	D_5 (51-55)	-	-0.24***	-0.09
	D_6 (70-74)	+	0.03**	0.01
	D_7 (76-80)	-	-0.07***	-0.02
	D_8 (95-99)	+	0.22***	0.09
Medium	D_1 (1-5)	-	-0.18***	-0.07
	D_2 (20-24)	+	0.02***	<0.01
	D_3 (26-30)	-	-0.04***	-0.02
	D_4 (45-49)	+	0.23***	0.09
	D_5 (51-55)	-	-0.22***	-0.09
	D_6 (70-74)	+	0.07***	0.03
	D_7 (76-80)	-	-0.04***	-0.02
	D_8 (95-99)	+	0.19***	0.08
Large	D_1 (1-5)	-	0.06***	0.02
	D_2 (20-24)	+	0.09***	0.03
	D_3 (26-30)	-	0.04**	0.02
	D_4 (45-49)	+	0.02	<0.01
	D_5 (51-55)	-	0.05	0.02
	D_6 (70-74)	+	0.06***	0.06
	D_7 (76-80)	-	-0.01	<-0.01
	D_8 (95-99)	+	-0.06***	-0.02

The dependent variable is a trade direction binary dummy that equals 1 is the trade is classified as a buy and 0 if it is classified as a sell. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider (the market makers). N refers to the total number of trades. Small and large refer to trades conducted at the smallest and biggest trade size quartiles, respectively. Medium trades refer to trade sizes that are between the 25th and 75th percentile. D_1 equals 1 for trades executed at the leftmost decimal digits 1-5, D_2 for 20-24, D_3: 26-30, D_4: 45-49, D_5: 51-55, D_6: 70-74, D_7: 76-80, D_8: 95-99. The subscript s that refers to assets trading under the minimum tick of 0.25 is dropped from this table. * significant at the 1% level.**

Table 6: The decision to trade above or below the minimum tick

Panel A: tick xx.25

	Order			
	Buy		**Sell**	
Variable	**Coefficient**	**Marginal effects**	**Coefficient**	**Marginal effects**
Constant	1.00***	-	1.74***	-
QS	1.73E-03	6.64E-04	-8.61E-03	-3.00E-04
Vol	0.34***	0.13	-0.84***	-0.29
Mom	-0.58***	-0.22	0.76***	0.27
OD	-0.35***	-0.14	-0.34***	-0.13
CD	0.23	0.09	-0.06***	-0.02
TS	-0.09***	-0.04	-0.16***	-0.05

Panel B: tick xx.50

	Buy		**Sell**	
Variable	**Coefficient**	**Marginal effects**	**Coefficient**	**Marginal effects**
Constant	0.27***	-	1.29***	-
QS	-1.03E-03	-4.07E-04	-2.47E-02**	-8.33E-03
Vol	0.43***	0.17	-0.36	-0.12
Mom	-0.80***	-0.32	0.23	0.08
OD	-0.32***	-0.13	-0.31***	-0.11
CD	0.07*	0.03	-0.08**	-0.03
TS	-0.02***	-0.01	-0.11***	-0.04

The dependent variable is a binary direction dummy variable that takes the value of one for orders conducted above the multiples of the minimum tick and zero below it. Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider (the market makers). $QS_{i,t}$ is the quoted spread measured as the half point difference between the ask and bid prices prior to any trade. $Vol_{i,t}$ is the absolute value of the average stock returns over the previous 30 minutes. $Mom_{i,t}$ is a momentum indicator variable that is calculated as the average stock return over the previous 30 minutes times one for buy orders or negative one for sell orders. OD_t and CD_t are opening and close dummies measured over the first and last 30 minutes of trading respectively. $TS_{i,t}$ is refers to the natural logarithm of trade size at the time of the trade. *, ** significant at the 1% and 5% levels respectively.**

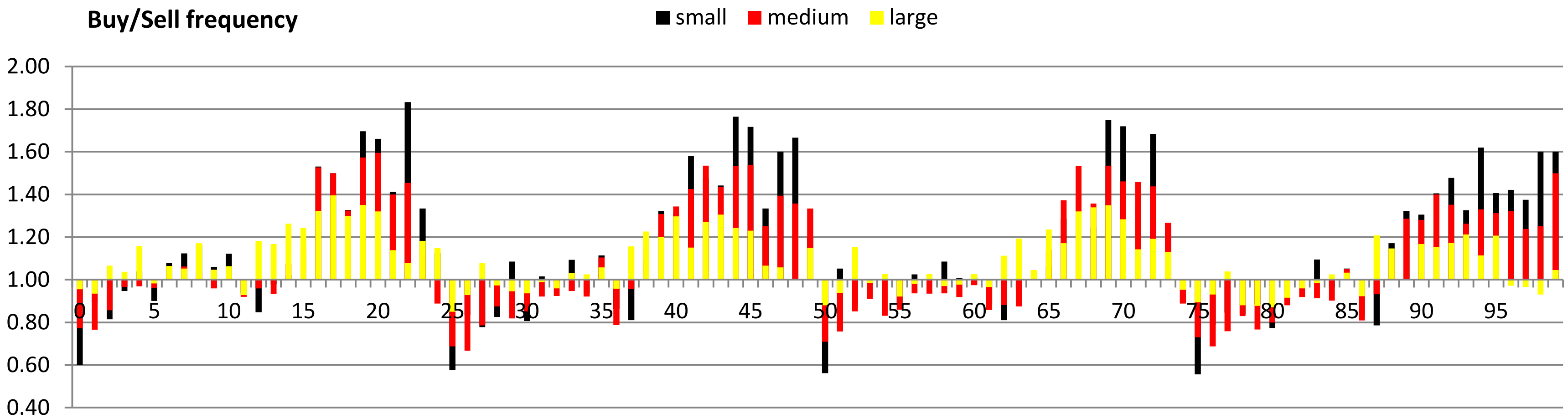
Table 7: Effective half-spread, price impact and realised spread estimates

	xx.25				xx.50			
	Buy		Sell		Buy		Sell	
	Above	Below	Above	Below	Above	Below	Above	Below
Panel A: Effective half-spread								
Small	0.02	0.08***	0.03	-0.03***	-0.01	0.11***	0.04	-0.01***
Medium	0.01	0.07***	0.03	-0.02***	0.03	0.06	0.02	-0.06***
Large	0.09	0.15***	0.09	0.03***	0.12	0.11	0.09	0.12**
Panel B: Price impact								
Small	0.04	0.04	-0.03	-0.05	< 0.01	0.06*	-0.01	< 0.01
Medium	0.03	0.01***	-0.03	-0.02	0.04	< 0.01	-0.02	-0.07*
Large	0.03	-0.02***	-0.06	-0.04*	-0.05	-0.07**	-0.09	-0.07
Panel C: Realised spread								
Small	-0.01	0.04***	0.06	0.02***	-0.01	0.05***	0.05	-0.02***
Medium	-0.02	0.06***	0.06	< 0.01	< 0.01	0.05***	0.05	0.01***
Large	0.06	0.17***	0.15	0.08***	0.17	0.18	0.18	0.19

The effective half-spread is calculated as the difference between the observed price and the midquote prior to the trade, standardised by the midquote price. We use midquotes that are posted at least 3 minutes before the trade (a maximum of 60 minutes). Trades that are conducted above the previous traded price are classified as buys, while trades that are conducted at a lower price are classified as sells. Trades are classified from the perspective of the liquidity provider (the market makers). Small and large refer to trades conducted at the smallest and biggest trade size quartiles, respectively. Medium trades refer to trade sizes that are between the 25th and 75th percentile. Price impact refers to the difference in quote midpoints between the current trade and trades reported at least 5 minutes after the announcement of the trade (a maximum of 60 minutes). The realised spread refers to the difference between the effective half-spread and price impact measures. T-tests for the pairwise equality of means are reported. *, **, * significant at the 10%, 5% and 1% levels respectively.**

Figure 1: Frequency distribution of the buy-to-sell ratio for small, medium and large trades conducted at the upstairs market

Panel A: xx.25



Panel B: xx.50

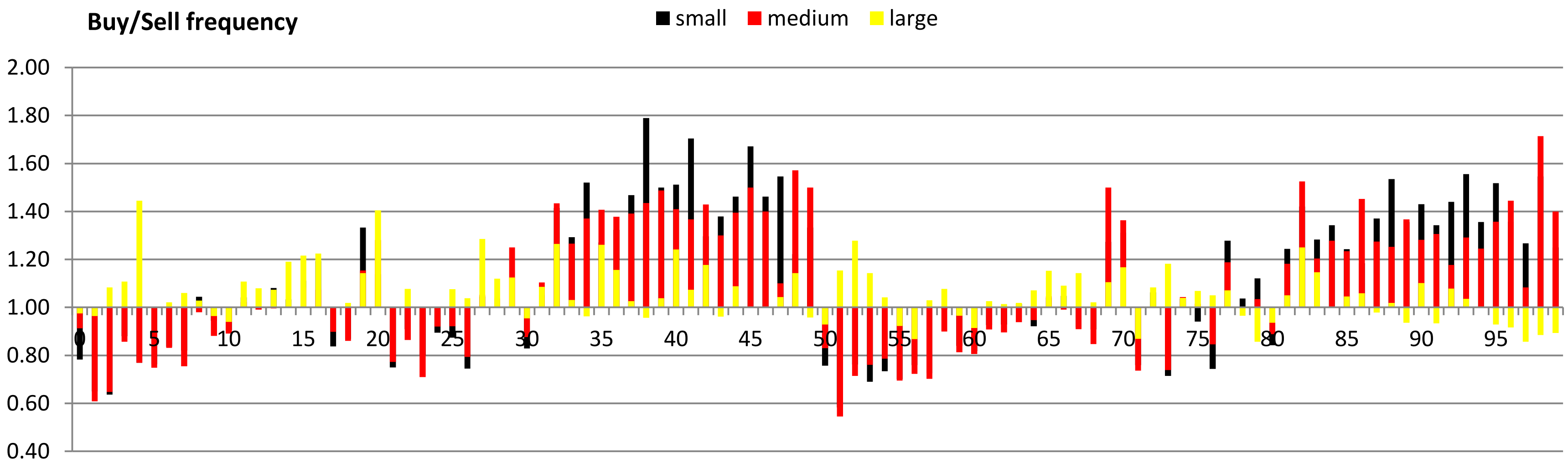
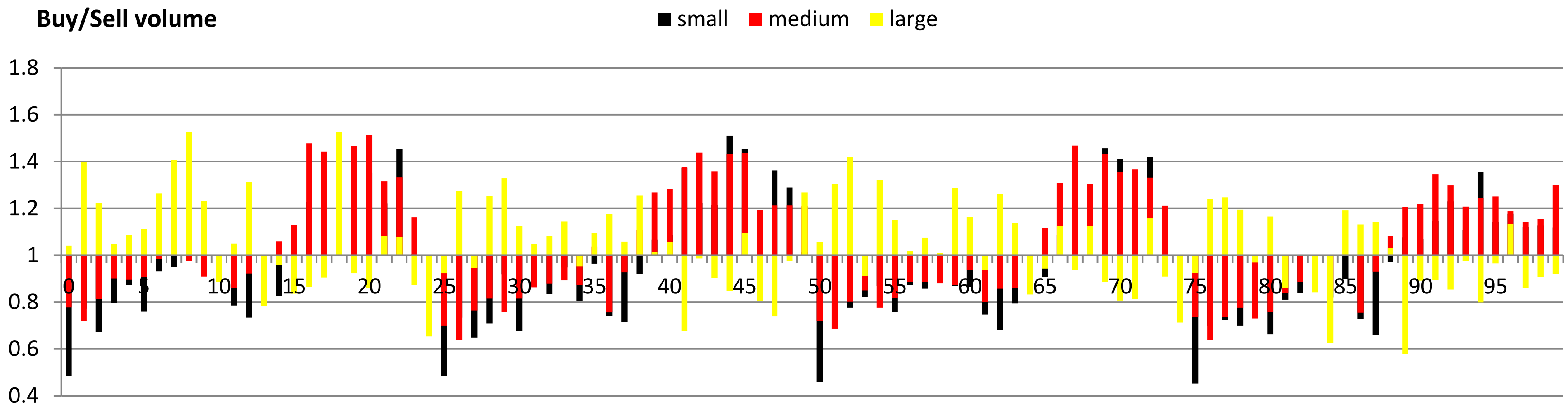


Figure 2: Volume distribution of the buy-to-sell ratio for small, medium and large trades conducted at the upstairs market

Panel A: xx.25



Panel B: xx.50